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Bandit-Aided Boosting

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Abstract

In this paper we apply multi-armed bandits (MABs) to accelerate ADABOOST. ADABOOST constructs a strong classifier in a stepwise fashion by selecting simple base classifiers and using their weighted “vote” to determine the final classification. We model this stepwise base classifier selection as a sequential decision problem, and optimize it with MABs. Each arm represent a subset of the base classifier set. The MAB gradually learns the “utility” of the subsets, and selects one of the subsets in each iteration. ADABOOST then searches only this subset instead of optimizing the base classifier over the whole space. The reward is defined as a function of the accuracy of the base classifier. We investigate how the MAB algorithms (UCB, UCT) can be applied in the case of boosted stumps, trees, and products of base classifiers. On benchmark datasets, our bandit-based approach achieves only slightly worse test errors than the standard boosted learners for a computational cost that is an order of magnitude smaller than with standard ADABOOST.

1 Introduction

ADABOOST [1] is one of the best off-the-shelf learning methods developed in the last decade. It constructs a classifier in a stepwise fashion by adding simple classifiers (called *base classifiers*) to a pool, and using their weighted “vote” to determine the final classification. The simplest base learner used in practice is the *decision stump*, a one-decision two-leaf decision tree. Learning a decision stump means to select a feature and a threshold, so the running time of ADABOOST with stumps is proportional to the number of data points n , the number of attributes d , and the number of boosting iterations T . When *trees* [2] or *products* [3] are constructed over the set of stumps, the computational cost is multiplied by an additional factor of the number of tree levels N or the number of terms m . Although the running time is linear in each of these factors, the algorithm can be prohibitively slow if the data size n and/or the number of features d is large.

There are essentially two ways to accelerate ADABOOST in this setting: one can either limit the number of data points n used to train the base learners, or one can cut the search space by using only a subset of the d features. Although both approaches increase the number of iterations T needed for convergence, the net computational time can still be significantly decreased. The former approach has a basic version when the base learner is not trained on the whole weighted sample, rather on a small subset selected randomly using the weights as a discrete probability distribution [1]. A recently proposed algorithm of the same kind is FILTERBOOST [4], which assumes that an oracle can produce an unlimited number of labeled examples, one at a time. In each boosting iteration, the oracle generates sample points that the base learner can either accept or reject, and then the base learner is trained on a small set of accepted points. The latter approach was proposed by [5] which introduces several feature selection and ranking methods used to accelerate ADABOOST. In

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particular, the LAZYBOOST algorithm chooses a fixed-size random subset of the features in each boosting iteration, and trains the base learner using only this subset.

In this paper we aim to improve the latter approach by “aiding” the random feature selection. It is intuitively clear that certain features are more important than others for classification. In specific applications the utility of features can be assessed a-priori (e.g., on images of characters, we know that background pixels close to the image borders are less informative than pixels in the middle of the images), however, our aim here is to *learn* the importance of features by evaluating their empirical performance during the boosting iterations. At the same time, in boosting it is important to keep a high level of base learner diversity, which is the reason why we opted for using *multi-armed bandits* (MAB) which are known to manage the exploration-exploitation trade-off very well.

MAB techniques have recently gained great visibility due to their successful applications in real life, for example, in the game of GO. In the classical bandit problem the decision maker can select an arm at each discrete time step [6]. Selecting an arm results in a random reward, and the goal of the decision maker is to maximize the expected sum of the rewards received. Our basic idea is to partition the base classifier space into subsets and use MABs to learn the utility of the subsets. In each iteration, the bandit algorithm selects an optimal subset, then the base learner finds the best base classifier in the subset and returns a reward based on the accuracy of this optimal base classifier. By reducing the search space of the base learner, we can expect a significant decrease of the complete running time of ADABOOST. case of decision stumps, we use the

The paper is organized as follows. First we describe the ADABOOST.MH algorithm and the necessary notations in Section 2. Section 3 contains our main contribution of using MABs for accelerating the selection of base classifiers. We present experimental results in Section 4, and conclude in Section 5.

2 ADABOOST.MH

For the formal description let $\mathbf{X} = (\mathbf{x}_1, \dots, \mathbf{x}_n)$ be the $n \times d$ *observation matrix*, where $x_i^{(j)}$ are the elements of the d -dimensional observation vectors $\mathbf{x}_i \in \mathbb{R}^d$. We are also given a *label matrix* $\mathbf{Y} = (\mathbf{y}_1, \dots, \mathbf{y}_n)$ of dimension $n \times K$ where $\mathbf{y}_i \in \{+1, -1\}^K$. In *multi-class* classification one and only one of the elements of \mathbf{y}_i is $+1$, whereas in *multi-label* (or *multi-task*) classification \mathbf{y}_i is arbitrary, meaning that the observation \mathbf{x}_i can belong to several classes at the same time. In the former case we will denote the index of the correct class by $\ell(\mathbf{x}_i)$.

The goal of the ADABOOST.MH algorithm ([1]) is to return a vector-valued classifier $\mathbf{f} : \mathcal{X} \rightarrow \mathbb{R}^K$ with a small *Hamming loss* $R_H(\mathbf{f}^{(T)}, \mathbf{W}^{(1)}) = \sum_{i=1}^n \sum_{\ell=1}^K w_{i,\ell}^{(1)} \mathbb{I} \left\{ \text{sign}(f_\ell^{(T)}(\mathbf{x}_i)) \neq y_{i,\ell} \right\}$ ¹ by minimizing its upper bound (the exponential margin loss)

$$R_e(\mathbf{f}^{(T)}, \mathbf{W}^{(1)}) = \sum_{i=1}^n \sum_{\ell=1}^K w_{i,\ell}^{(1)} \exp(-f_\ell^{(T)}(\mathbf{x}_i) y_{i,\ell}), \quad (1)$$

where $f_\ell(\mathbf{x}_i)$ is the ℓ th element of $\mathbf{f}(\mathbf{x}_i)$. ADABOOST.MH builds the final classifier \mathbf{f} as a sum of *base classifiers* $\mathbf{h}^{(t)} : \mathcal{X} \rightarrow \mathbb{R}^K$ returned by a *base learner* algorithm $\text{BASE}(\mathbf{X}, \mathbf{Y}, \mathbf{W}^{(t)})$ in each iteration t . In general, the base learner should seek to minimize the *base objective*

$$E(\mathbf{h}, \mathbf{W}^{(t)}) = \sum_{i=1}^n \sum_{\ell=1}^K w_{i,\ell}^{(t)} \exp(-h_\ell(\mathbf{x}_i) y_{i,\ell}). \quad (2)$$

Using the weight update formula of ADABOOST.MH, it can be shown that

$$R_e(\mathbf{f}^{(T)}, \mathbf{W}^{(1)}) = \prod_{t=1}^T E(\mathbf{h}^{(t)}, \mathbf{W}^{(t)}), \quad (3)$$

so minimizing (2) in each iteration is equivalent to minimizing (1) in an iterative greedy fashion. By obtaining the multi-class prediction $\hat{\ell}(\mathbf{x}) = \arg \max_{\ell} f_\ell^{(T)}(\mathbf{x})$, it can also be proven that the “traditional” multi-class loss (or *one-error*) $R(\mathbf{f}^{(T)}) = \sum_{i=1}^n \mathbb{I} \left\{ \ell(\mathbf{x}_i) \neq \hat{\ell}(\mathbf{x}_i) \right\}$ has an upper bound $K R_e(\mathbf{f}^{(T)}, \mathbf{W}^{(1)})$ if the weights are initialized uniformly, and $\sqrt{K-1} R_e(\mathbf{f}^{(T)}, \mathbf{W}^{(1)})$ with a multi-class initialization. This justifies the minimization of (1).

¹The indicator function $\mathbb{I} \{A\}$ is 1 if its argument A is true and 0 otherwise.

2.1 Learning the base classifier

In this paper we use *discrete* ADABOOST.MH in which the vector-valued base classifier $\mathbf{h}(\mathbf{x})$ is represented as $\mathbf{h}(\mathbf{x}) = \alpha \mathbf{v} \varphi(\mathbf{x})$, where $\alpha \in \mathbb{R}^+$ is the *base coefficient*, $\mathbf{v} \in \{+1, -1\}^K$ is the *vote vector*, and $\varphi(\mathbf{x}) : \mathbb{R}^d \rightarrow \{+1, -1\}$ is a *scalar* base classifier. It can be shown that for minimizing (2), one has to choose ϕ that maximizes the *edge* $\gamma = \sum_{i=1}^n \sum_{\ell=1}^K w_{i,\ell} v_\ell \varphi(\mathbf{x}_i) y_{i,\ell}$, using the votes

$$v_\ell = \begin{cases} 1 & \text{if } \sum_{i=1}^n w_{i,\ell} \mathbb{I}\{\varphi(\mathbf{x}_i) = y_{i,\ell}\} > \sum_{i=1}^n w_{i,\ell} \mathbb{I}\{\varphi(\mathbf{x}_i) \neq y_{i,\ell}\}, \\ -1 & \text{otherwise,} \end{cases} \quad \ell = 1, \dots, K. \quad (4)$$

It is also well known that the base objective (2) can be expressed as

$$E(\mathbf{h}, \mathbf{W}) = \sqrt{(1+\gamma)(1-\gamma)} = \sqrt{1-\gamma^2}. \quad (5)$$

In our experiments we used three base learners: decision stumps, decision trees, and products of decision stumps. The technical details of their implementations can be found in [3].

3 Using multi-armed bandits to reduce the search space

In this section we will first describe the MAB framework and the two particular algorithms we use. The next subsection contains our main contribution: we show how bandit algorithms can be used to accelerate the base learning step in AdaBoost.

3.1 Multi-armed bandits

In the classical bandit problem there are M arms that the decision maker can select at discrete time steps. Selecting arm j in iteration t results in a random reward $r_j^{(t)} \in [0, 1]$ whose (unknown) distribution depends on j . The goal of the decision maker is to maximize the expected sum of the rewards received. Intuitively, the decision maker's policy has to balance between using arms with large past rewards (exploitation) and trying arms that have not been tested enough times (exploration). The UCB algorithm [6] manages this trade-off by choosing the arm that maximizes the sum of the average reward $\bar{r}_j^{(t)} = \frac{1}{T_j^{(t)}} \sum_{t'=1}^t \mathbb{I}\{\text{arm } j \text{ is selected}\} r_j^{(t')}$ and a confidence interval term $c_j^{(t)} = \sqrt{\frac{2 \ln t}{T_j^{(t)}}}$, where $T_j^{(t)}$ is the number of times when arm j has been selected up to iteration t .

To avoid the singularity at $T_j^{(t)} = 0$, the algorithm starts by selecting each arm once. We also use a generalized version, denoted by $\text{UCB}(k)$, in which the best k arms are selected for evaluation, and the one that maximizes the actual reward $r_j^{(t)}$ is finally chosen.

The UCT algorithm [7] is a tree search method based on UCB. It is used often when the number of arms is large. UCT organizes the arms into a rooted tree-structure where the leaves represent the arms. In each time step, UCT determines a path from the root to a leaf by greedily choosing each inner point that maximizes the upper confidence bound $\bar{\varrho}_j^{(t)} + \sqrt{\frac{2 \ln T_{p_j}^{(t)}}{T_j^{(t)}}}$, where p_j is the

index of the parent of node j and $\bar{\varrho}_j^{(t)}$ is the average reward that has been obtained by all paths going through node j selected up to iteration t . When the path is selected, the reward obtained by the leaf node is assigned to each inner point in the path. Initially, neither the average reward nor the confidence interval are available. Trying all arms (as in UCB) would be computationally very inefficient; instead we use random rewards and confidence intervals for previously unvisited nodes.

3.2 The application of bandit-based methods for accelerating AdaBoost

The general idea is to partition the base classifier space into (not necessarily disjoint) subsets and use MABs to learn the utility of the subsets. In each iteration, the bandit algorithm selects an optimal subset (or, in the case of $\text{UCB}(k)$, a union of subsets). The base learner then finds the best base classifier in the subset, and returns a reward based on this optimal base learner. By reducing the search space of the base learner, we can expect a significant decrease of the complete running time of ADABOOST.

The upper bound (3) together with (5) suggest the use of $-\frac{1}{2} \log(1 - \gamma^2)$ for the reward. In practice we found that $r_j^{(t)} = 1 - \sqrt{1 - \gamma^2}$ works as well as the logarithmic reward; it was not surprising since the two are almost identical in the lower range of the $[0, 1]$ interval where the majority of the edges are. The latter choice has another advantage of always being in the $[0, 1]$ interval which is a formal requirement in MABs.

The actual partitioning of the base classifier set depends on the particular base learner. In the case of decision stumps, the most natural choice for UCB is to assign each feature to a subset. In principle, we could also further partition the threshold space but that would not lead to further savings in the linear computational time since, because of the changing weights $w_{i,\ell}$, all data points and labels would have to be visited anyway. On the other hand, subsets that contain more than one feature can be efficiently handled by $\text{UCB}(k)$.

In the case of trees and products we have more choices. We use UCB by considering each tree or product as a sequence of decisions, and using the same partitioning as with decision stumps at each inner node. In this setup we lose the information in the dependence of the decisions on each other *within* a tree or a product. A more natural choice for these base learners is to use UCT. In this solution we can consider each base classifier as a sequence, and use the tree-structured bandit for partitioning the (very large) sequence space. The partitioning follows naturally the sequence defined by the classification tree itself. The setup works also for products: even though the commutative product would suggest to represent *subsets* by arms, the greediness of the learning algorithm described in [3] makes *sequences* a more natural choice. Note that, in the case of trees, both (UCB and UCT) setups reduce the actual search space by construction since brothers having the same parent must act on the same feature (or one of a few number of features in $\text{UCB}(k)$) whereas, in general, brothers are independent.

4 Experiments

To test the algorithms, we carried out experiments on a synthetic set and five benchmark datasets using the standard train/test cuts². Beside MAB-based ADABOOST ($\text{UCB}(k)$ and UCT), we used two baselines: standard ADABOOST.MH with full search (FULL), and ADABOOST.MH with searching only a random subset of k features each time a decision stump is required ($\text{RANDOM}(k)$), that is, in each iteration when using decision stumps, and at each level when using trees or products. Instead of validating T and performing an early stopping, we decided to run the algorithm for a long time ($T = 10^5$ in each experiment), and measure the average of the test error (2) on the last $T/5$ iterations to obtain $\bar{R}(\mathbf{f}^{(T)}) = \frac{5}{T} \sum_{t=4T/5}^T R(\mathbf{f}^{(t)})$. The advantage of this approach is that this estimate is more robust in terms of random fluctuations after convergence than the raw error $R(\mathbf{f}^{(T)})$ at a given iteration. It is also a pessimistic estimate of the error when there is a slight over- or underfitting (since the average is always an upper bound of the minimum) which was rarely observed on these sets. The hyperparameters N and m were selected by 80%-20% simple validation on the training set using full ADABOOST.MH.

The first experiment was a simple test to validate the hypothesis that MABs may help ADABOOST to find “useful” features. We generated a 10-dimensional two-class data set in which only one of the features contained information about the labels³. As expected, full ADABOOST.MH (with decision stumps) used almost all the time the useful feature, whereas $\text{RANDOM}(1)$ and $\text{RANDOM}(3)$ used it in only 10% and 30% of the iterations, respectively. On the other hand, $\text{UCB}(1)$ and $\text{UCB}(3)$ found the good feature in 17.5% and 90% of the iterations, respectively.

Table 1 shows the asymptotic test errors on the benchmark datasets after 10^5 iterations. The first observation is that full ADABOOST.MH wins most of the times although the differences are rather small. The few cases where RANDOM or UCB/UCT beats full ADABOOST.MH could be explained by statistical fluctuations or the regularization effect of randomization. Secondly, UCB/UCT seems slightly better than RANDOM although the differences are even smaller. The difference seems more significant on the MNIST set where the number of features is rather large and some of the features are known to be useless.

Our main goal was not to beat full ADABOOST.MH in test performance, but to improve its computational complexity. So we were not so much interested in the *asymptotic* test errors but rather the speed by which *acceptable* test errors are reached. As databases become larger, it is not unimaginable that certain algorithms cannot be run with their statistically optimal hyperparameters (T in our case) because of computational limits, so managing *underfitting* (an algorithmic problem) is more important than managing overfitting (a statistical problem) [8]. To illustrate how the algorithms be-

²The data sets (selected based on their wide usage and their large sizes) are available at yann.lecun.com/exdb/mnist (MNIST), www.kernel-machines.org/data.html (USPS), and www.ics.uci.edu/~mllearn/MLRepository.html (letter, pendigit, isolet).

³ $x_i^{(j)}$ is random uniform in $[0, 10]$, and $y_i = 2(\lfloor x_i^{(1)} \rfloor \bmod 2) - 1$.

learner \ data set	MNIST	USPS	UCI pendigit	UCI isolet	UCI letter
Stump/FULL	7.76 (0.02)	6.58 (0.04)	5.06 (0.03)	4.99 (0.03)	14.82 (0.04)
RANDOM(1)	7.39 (0.03)	6.27 (0.03)	5.87 (0.03)	4.60 (0.07)	16.91 (0.04)
RANDOM(5)	7.62 (0.05)	6.40 (0.03)	5.04 (0.04)	4.56 (0.03)	14.82 (0.03)
RANDOM(10/20)	7.70 (0.04)	6.55 (0.04)	5.07 (0.03)	4.98 (0.05)	14.82 (0.04)
UCB(1)	7.35 (0.03)	6.41 (0.04)	5.31 (0.04)	4.51 (0.04)	14.81 (0.06)
UCB(5)	7.35 (0.03)	6.50 (0.07)	5.07 (0.03)	4.76 (0.07)	14.73 (0.04)
UCB(10/20)	7.69 (0.04)	6.57 (0.04)	5.00 (0.03)	4.84 (0.04)	14.76 (0.03)
Product (m)	3	3	2	6	10
FULL	1.26 (0.01)	4.26 (0.03)	1.91 (0.01)	3.99 (0.06)	2.33 (0.02)
RANDOM(1)	1.85 (0.03)	4.51 (0.06)	2.09 (0.02)	3.81 (0.05)	3.23 (0.03)
RANDOM(5)	1.83 (0.03)	4.74 (0.04)	2.14 (0.00)	3.53 (0.05)	3.36 (0.04)
RANDOM(10/20)	1.88 (0.03)	4.52 (0.02)	2.26 (0.02)	3.88 (0.08)	2.33 (0.02)
UCB(1)	1.85 (0.03)	4.69 (0.04)	2.03 (0.02)	3.72 (0.07)	2.34 (0.02)
UCB(5)	1.49 (0.02)	4.64 (0.08)	2.00 (0.02)	3.75 (0.07)	2.22 (0.03)
UCB(10/20)	1.32 (0.01)	4.59 (0.04)	1.97 (0.02)	3.83 (0.03)	2.46 (0.02)
UCT	1.75 (0.04)	5.13 (0.04)	1.88 (0.01)	4.22 (0.06)	2.22 (0.03)
Tree (N)	17	15	19	8	38
FULL	1.52 (0.02)	4.75 (0.02)	2.14 (0.04)	3.87 (0.03)	3.20 (0.02)
RANDOM(1)	2.11 (0.03)	5.24 (0.02)	2.46 (0.01)	3.89 (0.04)	4.25 (0.02)
RANDOM(5)	1.90 (0.03)	5.19 (0.02)	2.50 (0.01)	3.84 (0.04)	4.27 (0.03)
RANDOM(10/20)	1.85 (0.03)	5.28 (0.01)	2.46 (0.01)	3.84 (0.07)	4.34 (0.03)
UCB(1)	2.23 (0.03)	5.27 (0.08)	2.23 (0.01)	4.01 (0.03)	3.42 (0.04)
UCB(5)	2.00 (0.01)	5.03 (0.01)	2.26 (0.01)	3.92 (0.04)	3.26 (0.03)
UCB(10/20)	2.21 (0.04)	4.95 (0.04)	2.13 (0.01)	3.79 (0.05)	2.73 (0.05)
UCT	2.31 (0.04)	5.86 (0.04)	2.20 (0.00)	4.53 (0.06)	3.54 (0.03)

Table 1: Asymptotic test error percentages $100\bar{R}(\mathbf{f}^{(T)})$ with $T = 10^5$ on benchmark datasets.

have in terms of computational complexity, we plot the smoothed test error curves $\bar{R}(\mathbf{f}^{(T)})$ versus *time* for selected experiments in Figure 1. The improvement in terms of computational time over full ADABOOST.MH is often close to an order of magnitude (or two in the case of MNIST). Comparing the algorithms in a more quantitative manner is not straightforward since we have to decide how to handle the speed/performance trade-off. In Table 2 we show how long it takes for the different algorithms to reach 1.2 (1.8 for MNIST) times the asymptotic error of full ADABOOST.MH. The results show that most of the time, MAB-based boosting is significantly faster than both full ADABOOST.MH and RANDOM(k).

learner \ data set	MNIST	USPS	UCI pendigit	UCI isolet	UCI letter
Stump/Full	18000	708	127	11100	774
RANDOM(10/20)	565	518	84	792	683
UCB(10/20)	268	447	45	446	685
Product/Full	747000	16700	1110	140000	19100
RANDOM(10/20)	226000	2650	236	7540	11700
UCB(10/20)	26400	2040	54	6300	18900
UCT	44400	2270	337	710	5660
Tree/Full	1209000	3240	521	15300	9830
RANDOM(10/20)	95800	568	501	7970	10300
UCB(10/20)	60700	369	297	2500	1770
UCT	∞	402	459	894	7330

Table 2: Time (in second) to reach 1.2 (1.8 for MNIST) times the asymptotic error of full ADABOOST.MH.

5 Conclusion

In this paper we asked a simple question: can ADABOOST be accelerated by modeling it as a sequential decision problem, and optimizing it within this framework? To answer, we chose a particular

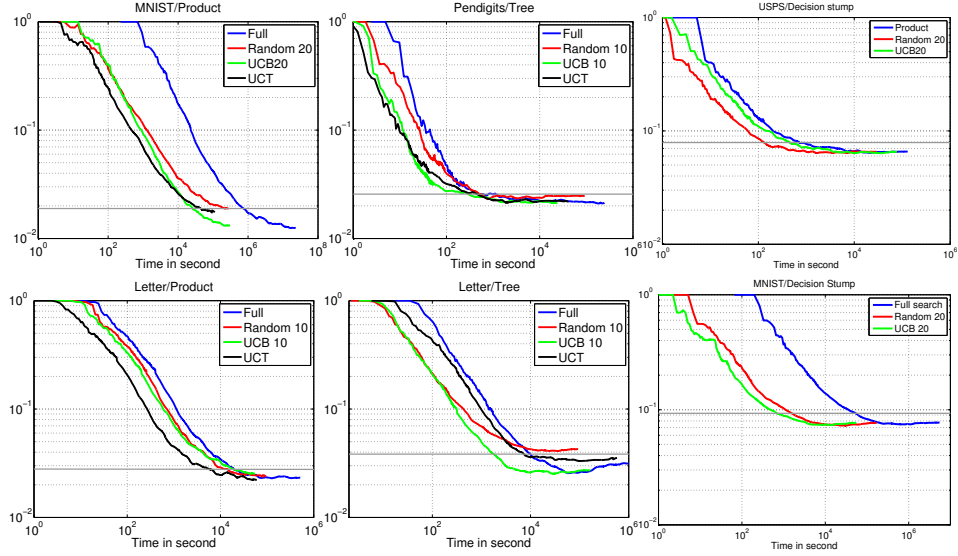


Figure 1: Smoothed test errors $\bar{R}(\mathbf{f}^{(T)})$ vs. total computational time. The horizontal line indicates 1.2 (1.8 for MNIST) times the asymptotic error of full ADABOOST.MH.

setup (multi-armed bandits), and made several modeling and algorithmic choices within the framework. Since our goal was to improve the speed of ADABOOST, most of our choices are justified by arguments of algorithmic simplicity and computational complexity. On the other hand, to keep the project within manageable limits, we consciously did not explore all the possible avenues. For example, multi-armed bandits assume a *stateless* system, whereas ADABOOST has a natural state descriptor: the weight matrix $\mathbf{W}^{(t)}$. In this setup a Markov decision process would be more natural choice.

Our answer to the original question is two-fold: it seems that the asymptotic test error of ADABOOST with full search is hard to beat, so if we have enough computational resources to reach the flattening of the test error curve, we should use full ADABOOST. On the other hand, in *large scale learning* (recently publicized in a seminal paper by Bottou and Bousquet [8]), where we stay in an *underfitting* regime and so fast optimization becomes more important than asymptotic statistical optimality, our MAB-optimized ADABOOST can find its niche.

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